

Eco-efficiency determinants: a new approach combining an agronomic whole-farm model and efficiency frontier analysis

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Abstract :

The growing awareness on the multiple environmental impacts of livestock production has risen the necessity to widen the definition of efficiency to a multidimensional eco-efficiency concept. Our paper suggests a combined approach of a whole-farm agronomic model and frontier efficiency method to explore deeply the determinants of eco-efficiency. The whole-farm model used, GAMEDE, is randomly parameterized for key management practices and structural parameters in order to generate a large dataset of simulated dairy systems in La Réunion Island. Upper and lower bounds fixed for the stochastic choice of parameter values are a key point in the approach and relies on expert knowledge derived from participatory modeling. For each simulation, numerous indicators describing the functioning and the performance of the production system are model-based calculated and some of them (inputs, outputs and undesirable outputs) are chosen to define the production technology in a frontier efficiency analysis. The frontier efficiency method used, data envelopment analysis, provides a multidimensional synthetic eco-efficiency score. It represents the potential outputs raise, with no increase in inputs and undesirable outputs. The eco-efficiency score can be linked to all the indicators of the production system calculated by the whole-farm model and it becomes possible to characterize accurately the factors (managerial, structural, economic, agro and zootechnical, etc) explaining eco-efficiency levels. In our study case, dairy farming in La Réunion, livestock production is strongly constrained by land scarcity. Consequently most eco-efficient farms appear to be intensive systems with important forage productivity to ensure their alimentation self-sufficiency. While most efficiency studies are restricted to narrow data set, the proposed methodology is innovative as it allows to cover the realm of possible livestock production systems in a given territory and characterize them, at low cost in time and money, with a large range of descriptive variables. Coupling whole-farm models and efficiency frontier analysis is a promising methodology to better identify the eco-efficiency determinants and the ecological intensification pathways.

Keywords: Eco-efficiency, Combined modeling, whole-farm model, frontier efficiency, dairy systems

1 Introduction

In response of the challenge of increasing by 85% the global demand of meat, The Food and Agriculture Organization (FAO) launched in 2011 a global agenda of action in support of the sustainable livestock sector development. One of the three pillars of the project is focused on “closing the efficiency gap” (FAO, 2012) as many reports emphasized the major difference between various agricultural systems in ecological efficiency (for example in the dairy sector, greenhouse gas emissions may range from 1.3 to 7.5 Kg CO₂-eq per liter of milk). Thus, ecological intensification (Dalgaard et al., 2003) has become a keystone in the agricultural research and agricultural system modeling is now widely implemented to design future sustainable production systems (Godfray et al., 2010).

Agricultural system modeling is a wide research field. This field is continuously enriched by the growing knowledge on biophysical processes. For instance models describe more and more precisely the feed/nutrient requirements of animals/plants and corresponding production (e.g. for animals: INRATON; INRA, 2007; e.g. for plants STICS; Brisson et al., 2003). From this strictly biophysical approach, simulation models evolved toward more complex forms, in order to represent accurately agricultural systems functioning or management. Rotz and Coiner (2006) and Vayssières et al. (2009a) insisted on the necessity to model explicitly the interaction between human activities and biophysical processes to be able to represent realistically the management of farming systems. Additionally, the authors emphasize the limit of models at herd or plot scale and explain that only whole-farm models can assess the impact of a modification (technical or managerial) on the production system performances (Vayssières et al., 2011). Other whole-farm models available in the literature are IFSM (Rotz and Coiner, 2006), MELODIE (Chardon et al., 2012), NUANCES-FARMSIM (Giller et al., 2006), etc. These models try to reflect the interactions in the production systems, between all the sub-systems (humans, plants, animals, soils...) under several environments (climate, markets...). Although whole-farm models can describe accurately the functioning or the management of the production system, they require a various number of parameters and are most of the time limited to “what if” (simulation models) or “how to” (optimization models) questions.

In the respect of the agroecological paradigm to produce more and jointly reduce environmental impact, operational research has been involved in the reflection to reconsider agricultural modeling. Indeed, frontier efficiency analysis methods and specifically the non-parametric one called data envelopment analysis (DEA, Charnes et al., 1978) has brought a new vision on environmental assessment in agricultural production systems. The introduction of the undesirable outputs in the classical DEA models (Scheel, 2001; Coli et al., 2011) provides a powerful method to assess the eco-efficiency on the basis of synthetic databases. Non-parametric frontier efficiency method doesn't assume any functional form of the technology production and only needs the definition of a set of inputs, desirable outputs and undesirable outputs. Based on linear programming, the model defines an efficiency score based on the distance between a farm and the benchmark. This way, the model allows a multidimensional definition of the eco-efficiency, i.e. considering multiple inputs, outputs and undesirable outputs. Eco-efficiency is broadly defined by the World Business Council for Sustainable Development (WBCSD, 2011) as “[...] the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity”. In this paper, eco-efficiency refers to a micro-economic approach of eco-efficiency (maximization of outputs joint to a minimization of inputs and undesirable outputs) which meets two objectives among those identified by the WBCSD regarding eco-efficiency: (i) reduce the

consumption resources, (ii) reduce the impact on nature, (iii) provide customers with higher quality products and services.

According to Goffinet's (2006) definition, a model is a "reconstruction of a process based on data and knowledge, for a given objective". Agronomic models and the DEA method used by economist are two types of models with very different purposes. On one hand, whole-farm agronomic models are complex and they fail to simplify the production process because their objectives are to represent as accurately as possible the reality and to be able to simulate and explore alternative production systems (ex-ante analysis). On the other hand, efficiency analyses thanks to the DEA method promote the Occam's razor principle to introduce as few hypotheses as possible and only assume a production technology with limited knowledge on the production process, but achieve to determine a multidimensional progress margin in each dimension (inputs, desirable outputs, undesirable outputs). Here, we see that in this paper, we present an original methodology combining agronomic simulation models with the DEA method in order to fully characterize the eco-efficiency determinants of agricultural systems.

As this paper involves parameters choice among bounds and many simulations launches, combined with an optimization method, our theoretical framework is close to various modeling techniques as sensitivity analysis, inverse modeling, or even simulation-based optimization.

Sensitivity analysis and uncertainty analysis has emerged as impossible steps to circumvent in a modelling research and specifically in the model validation. Uncertainty analysis focuses on the evaluation of uncertainty in all model components (parameters, equations, inputs data...) and provides confidence interval on each output (Monod et al., 2006). Sensitivity analysis is more focused on the global behavior of the model and on the influence of each component in the final simulated result. A specific output is considered to assess the impact of specific value of parameters in local sensitivity analysis while the whole range of outputs value is assessed according to inputs realm of possible in global sensitivity analysis (Zhan et al., 2013). Globally, these modelling approach are dedicated to control the uncertainty on the data used or manage the role of each component in the overall model implementation.

As described by Tarantola (2005), inverse problem "consists of using the actual result of some measurements to infer the values of the parameters that characterize the system". Inverse modeling has been a great support in the research field involving large amount of data and very complex models, typically in atmospheric research (Vautard et al., 2000). Most recently, with the development of holistic models in agronomy, inverse modeling has been applied in the context of crop production in western Kenya (Tittonell, 2007). Indeed, inverse modeling allows identifying robust value of parameters according to their ability to predict accurately an observable data through the modeling process. In other words, the basic principle of inverse modeling is to identify the value of a set of unknown parameters, by testing various combinations and define which combination leads to the simulated outputs closer to the observed ones. In this sense, the aim of inverse modeling is mainly to correctly parameterize a complex model.

The two approaches differ to our methodology as our objective is not about identifying the accurate value of parameters nor testing the sensibility of model indicators or parameters, but to generate the realm of possible systems through a stochastic choice of parameters values between upper and lower bounds. Our methodology doesn't rely on inverse modeling and sensitivity analysis but belongs to simulation-based optimization (SBO, Mattot et al., 2012). Even if our methodology is closely linked to SBO, we argue that DEA is not only an optimization method, but also a microeconomic tool relying on economic (as disposability) and mathematic (convex production set) assumptions to determine the eco-efficiency level. As Azadeh et al. (2008) perform on railway system, combining DEA with a simulation model is neither inverse modelling nor SBO but a methodology that could be called simulation-based Data Envelopment Analysis. Even though, to our

knowledge, this modelling methodology has never been implemented in agricultural systems research. To conclude this terminology specification about modelling, we see that our research is closer to inverse modeling or sensitivity analysis in the combination of simulation and optimization but don't follow the aim goal to refine the parameters value. In this paper, we consider that the simulation model (GAMEDE) describe the production process as accurately as possible, thus, our objective is not to implement Monte Carlo analysis or sensitivity analysis to explore the model , but simply to use its accurate description of the biophysical processes and decisional systems to generate simulated production systems.

The methodology is applied to explore dairy livestock systems, in a French overseas department in the Indian Ocean, La Réunion. Actually, land scarcity is the major issue for livestock production in this insular territory where most of the agricultural land is allocated to sugar cane production (D'Haese et al., 2009). Dairy farms are intensive production systems based on an important use of concentrate feeds and mineral fertilizers, thus nitrogen surplus management is a key issue for livestock development in La Réunion (Vayssières et al, 2009b). The island face the challenge to raise its self-sufficiency in livestock products, to feed more than 1 million person in 2040 with a limited access to costly imported feed products from mainland France. In this context, eco-efficiency assessment can be helpful to identify progress margins for the current dairy production systems and identify ecological pathways.

Consequently our paper pursues two goals: a methodological one and an empirical one. The methodological issue is to use a whole-farm model to generate for the first time a simulated dataset of dairy farms, implement an efficiency assessment thanks to frontier analysis, and give recommendations according to this first experience. Empirically, the paper assesses the determinants (structural and managerial) of efficiency in the specific agronomic context of insular tropical livestock production.

This paper is divided in three parts. The first one describes the whole proposed methodology and details the model used for simulations and the DEA method used for production system scoring. In a second one, results and knowledge generated at the different steps of the proposed methodology are detailed. Finally, the third part discusses the main assets and limits of the proposed methodology and some recommendations are pointed out for further eco-efficiency analysis.

2 Material and methods

2.1 Combining a simulation model and the DEA method

The proposed methodology combines simulation modeling and Data envelopment analysis (DEA) for analyzing efficiency. It is a three steps methodology (figure 1). In a first step, a whole-farm model, GAMEDE here, is solicited to generate a set of simulated farms based on random parameterization. In a second step, the efficiency level of each farm is assessed thanks to the DEA method. And the third step aims to link the multidimensional DEA scores with the characteristics of the corresponding production systems on the basis of a multivariate analysis.

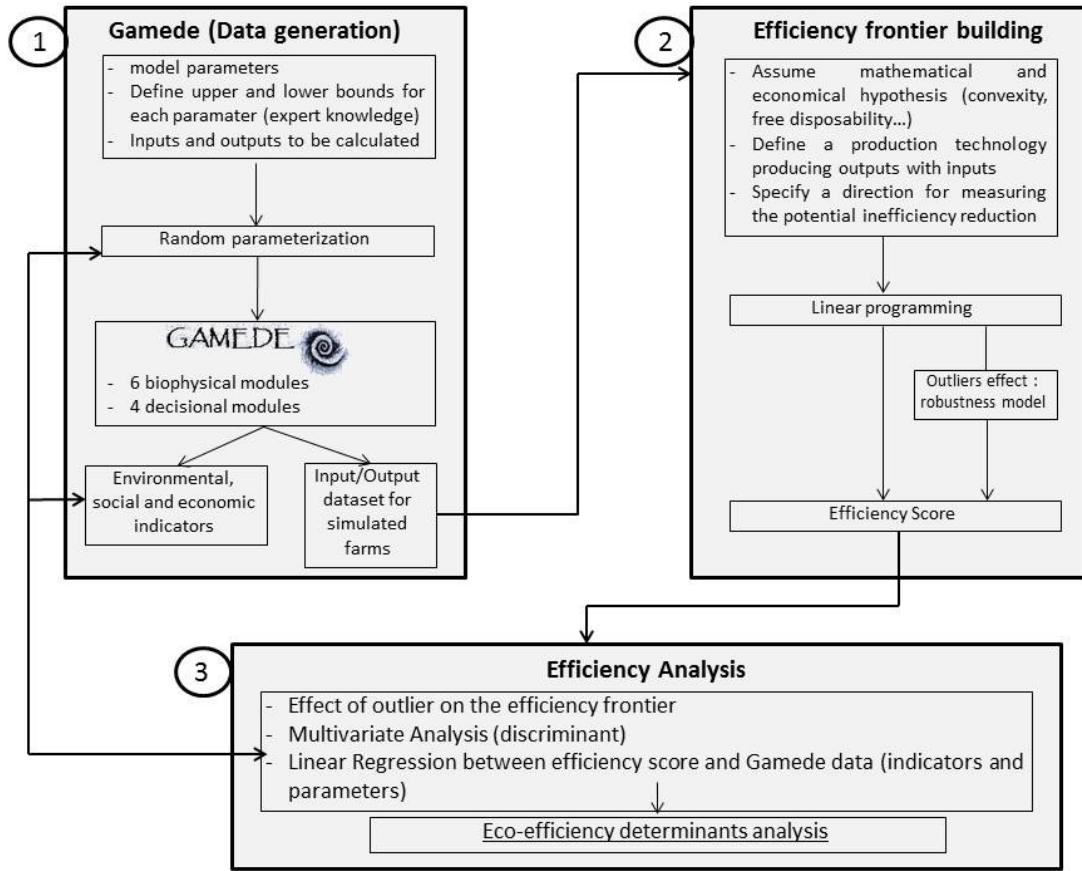


Fig. 1. Three-stage methodology for analyzing the efficiency of farming systems.

Acknowledging that variable nomenclature may be confusing, since some outputs of the GAMEDE model (i.e. indicators) are used as inputs for the DEA method, figure 2 summarizes variables taken into account in the proposed methodology in order to clarify the terminology of this paper.

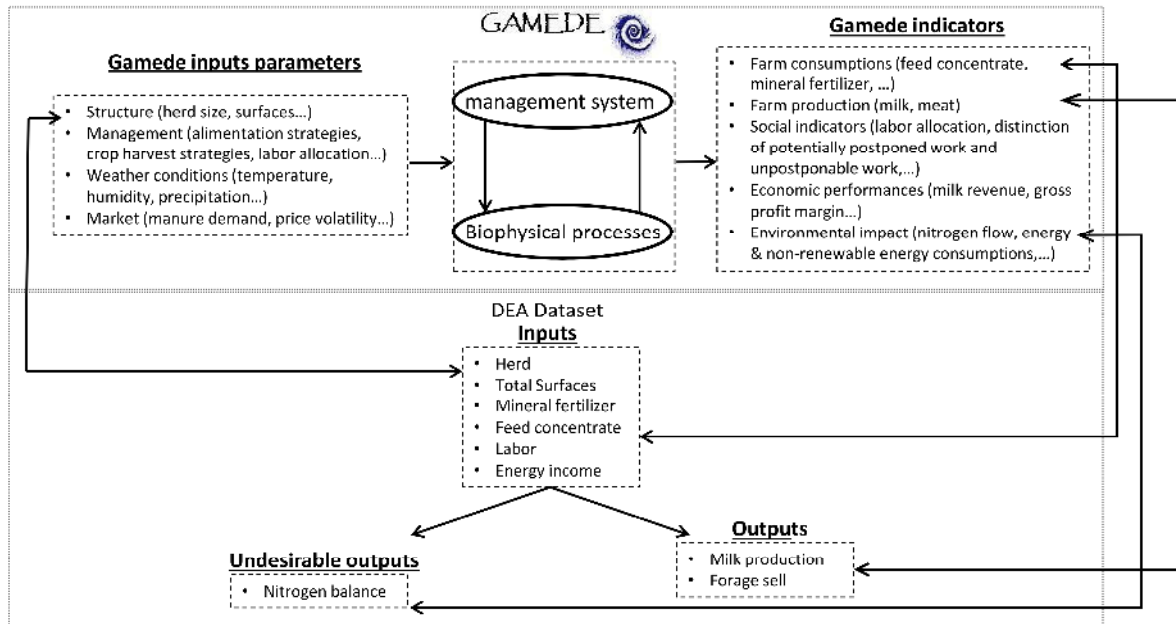


Fig. 2. Overview of data in GAMEDE and in DEA model used in the proposed methodology

2.2 *Data generation with the GAMEDE model*

GAMEDE is the material support of the simulations related in this paper. GAMEDE is a dynamic simulation model representing the farm agro-ecosystem. It includes 26,950 variables and 1950 equations that at one moment depend on variables at another moment, representing the changes in the state of the system over time. GAMEDE biophysical modules are based on the recognized mechanistic models MCP (Leteinturier et al., 2004), MOSICAS (Martiné, 2003), INRATION (INRA, 2007), CNCPS (Fox et al., 2004), SEPATOU (Cros et al., 2003) and GRAZEIN (Delagarde et al., 2004). The decision system model was designed on the basis of knowledge we have about a large number of actual dairy farms (40 farms used to make a farm typology) and an in-depth description of management practices of six representative dairy farms surveyed during 4 years. From a technical point of view, GAMEDE is implemented on Vensim® modelling and simulation software in its DSS32 version 5.4a.

2.2.1 *GAMEDE input parameters*

In GAMEDE, five types of parameters have to be specified: management practices (farmer's strategy on forage crop, feed ration etc...), farm structure (storage capacity for feed and manure, forage plot composition...), herd (milk composition, period of calving...), weather (specific for each type of farms) and external resources availability (mainly to fix the purchase and sale opportunities), as shown in figure 2. This way, it is possible to simulate realistically the functioning of the production system (Vayssières et al., 2009b).

2.2.2 *The core of the model*

Ontologically, GAMEDE is a stock-flow model. The core of the model and the whole ontology of GAMEDE are based on the causal-chain between practices, biophysical processes and sustainability of the production system. First, the management system of GAMEDE simulates technical actions according to the farmer's action plan and operational decision rules, the state of the production and the farm's environment (daily weather and availability of external resources). Secondly, the biophysical system of GAMEDE simulates consequences of these technical actions on main biophysical processes and translates them into biomass flows depending on weather conditions.

2.2.3 *GAMEDE outputs*

GAMEDE assesses the sustainability of the simulated dairy farming systems according to technical, environmental, social and economic indicators (figure 2). The technical indicators concern main farm consumptions (concentrate feeds, mineral fertilisers, etc) and productions (forage and milk). Forage production is the total feed energy harvested by ensiling, cutting and carrying, or direct grazing of forage, on the total utilised agricultural area (in UF year⁻¹). UF is the feed unit defined by the french UF/PDI feeding unit system (Jarrige, 1989) characterising the energy value of a considered feed to allow milk production or weight gain. Milk production is expressed in liter. As environmental indicators, the model calculates annual N leaks to the environment and apparent N farm gate balance (Nevens et al., 2006). Non-renewable energy consumptions (in MJ year⁻¹) consider both direct and indirect consumptions. The social indicator is the total labour requirement. Hours of labour are linked to each technical operation to represent direct influence of practice on labour requirement. The economic indicator, gross margin (in €year⁻¹) is appropriate for analysing contributions of activities to farm economic viability (De Jager et al., 2001). Usually, these indicators calculated by GAMEDE are directly used to evaluate and design more sustainable production systems (Vayssières et al.,

2009b). In this paper, the authors use these indicators to build the dataset at the origin of the efficiency frontier, also called the DEA dataset (see figure 2).

2.2.4 *Random parameterisation of GAMEDE and dataset generation*

In the proposed methodology, the DEA dataset generation is based on a randomly parameterization of the GAMEDE model. In other words, values of inputs parameters are defined by Monte Carlo Simulation, i.e. generated by a stochastic function with a given distribution. For simplification, a uniform normal distribution was used in this study but knowledge on observed systems can lead to use other types of distribution. The “Monte Carlo Simulation” application of the VENSIM Software, was used here for data generation. It is technically possible to simulate as much simulated farms as we desire because the application doesn’t fix limits. We simulated here 5000 farms for a reason of time limitation (about 1 minute per simulation with GAMEDE).

Main issues of the data set generation are the selection of key model input parameters and the lower and upper bounds of the distribution. In this study case, only intrinsic sources of progress in efficiency were considered. The hypothesis was that farm performances, efficiency in particular, are mainly determined by managerial and structural changes because the pedo-climatic and socio-economic context of the tropical island is relatively stable and more difficult to change. Consequently, only two types of GAMEDE inputs were randomly parameterized: management practices (e.g. duration between two forage crop harvests, quantity of concentrate feeds in the feed ration...) and farm structural parameters (e.g. herd size, agricultural areas...). Other GAMEDE input parameters, i.e. weather and market parameters, were considered as constant. Our main objective considering these two types of parameters is to analyze whether the efficiency is equally explained by structural or managerial changes in the production process. For each variable parameter, the definition of the lower and upper bounds relied on observed ranges for actual 40 farms (Alary et al., 2002) crossed with expert knowledge of local technical advisers. This way, we can guaranty that each value was realistic for dairy production systems in the agronomic context of La Réunion. Table 1 exposes the inputs parameters chosen and their ranges.

Each GAMEDE launched with a stochastic value of parameters simulate a dairy production which can be monitored through indicators described in 2.2.3. Considering the large amount of indicators available in GAMEDE, we decided to focus on those assumed to be involved in eco-efficiency in dairy production (alimentation, nitrogen management, forage production...). Indicators considered in the multivariate analysis to explain eco-efficiency levels are presented in Table 2.

Table 1

Input parameters of GAMEDE stochastically determined between lower and upper bounds

	Parameters	Description	Unity	Min	Max
Structural parameters	GS	Total grassland surfaces	ha	0	50
	SCS	Total sugar cane surfaces	ha	0	20
	MSC	Manure stockage capacity	Kg	0	20000
	H	Herd	animals	0	150
Forage management	ISH	Time interval between two summer harvest (mean)	Day	50	75
	TIGH	Theoretical interval between two grassland harvest (mean)	Day	30	80
	TIPG	Theoretical interval for pasturage regeneration (mean)	Day	30	90
	ISCSH	Time interval between two sugar cane harvest (mean)	Day	360	370
	TISCH	Theoretical interval between two sugar cane harvest (mean)	Day	320	380
	MaFGS	Manure fertilization of grassland in summer	Kg of fresh matter per day per ha	0	110000
	MiFGS	Mineral fertilization of grassland in summer	Kg of dry matter per day per ha	0	500
	MaFGW	Manure fertilization of grassland in winter	Kg of fresh matter per day per ha	0	110000
	MiFGW	Mineral fertilization of grassland in winter	Kg of dry matter per day per ha	0	500
Fertilizer management	MaFSCS	Manure fertilization of sugar cane in summer	Kg of fresh matter per day per ha	0	70000
	MiFSCS	Mineral fertilization of sugar cane in summer	Kg of dry matter per day per ha	0	500
	MaFSCW	Manure fertilization of sugar cane in winter	Kg of fresh matter per day per ha	0	70000
	MiFSCW	Mineral fertilization of sugar cane in winter	Kg of dry matter per day per ha	0	500
	FCS1	Forage composition for dairy cows in season 1	Kg of fresh matter per day per ha	100	300
	CFS1	Concentrate feed composition for dairy cows in season 1	Kg of fresh matter per day per ha	0	17
	FCS2	Forage composition for dairy cows in season 2	Kg of fresh matter per day per ha	100	300
	CFS2	Concentrate feed composition for dairy cows in season 2	Kg of fresh matter per day per ha	0	17
Feed management	FCS3	Forage composition for dairy cows in season 3	Kg of fresh matter per day per ha	100	300
	CFS3	Concentrate feed composition for dairy cows in season 3	Kg of fresh matter per day per ha	0	17

Table 2

GAMEDE indicators selected to explain eco-efficiency of simulated farms

Indicators	Description	Unity
M	Milk production	liter
AS	Animals sell	Animals
LC	Lended calves	Animals
FS	Forage sell	Kg of fresh matter
GPM	Gross profit margin	Euros
NB	Nitrogen balance	Kg of nitrogen per Ha
CLI	Crop-livestock interaction	N export (Kg N /day) / N total flows(Kg N /day)
L	Labor	hours
CFI	Concentrate feed importation	Kg of fresh matter
MFI	Mineral Fertilizer importation	Kg of fresh matter
NE	Nitrogen efficacy	N export (Kg N) / N import (Kg N)
SND	System nitrogen dependency	Nitrogen import (Kg N) / N total flows(Kg N /day)
SBO	System biological orientation	From 0 (only meat) to 1 (only milk)
ASS	Alimentation self-sufficiency	Self-produced alimentation / Total alimentation
FSS	Fertilizer sel-sufficiency	Self-produced nitrogen used / Total nitrogen used
NGE	Nitrogen gaseous emissions	Kg of Nitrogen per day
EGP	Ensiled grassland productivity	wrapped silage bales per Ha per year
UFLP	UFL produced	UFL per Ha per year
GP	Grassland productivity	Kg of dry matter per Ha per year
MP	Milk productivity	Liter of milk per dairy cow per year
EEF	Energetic efficacy	Energy export (MJ) / Energy import (MJ)
FPLM	Fuel used for milk production	fuel equivalent per hectoliter of milk
EEX	Energy exportation	MJ

2.3 Frontier efficiency assessment

2.3.1 Frontier efficiency basic principles

We use in this paper a non-parametric approach to assess the efficiency of simulated farms. We choose to implement Data Envelopment Analysis (DEA) which allows measuring the efficiency of Decision Making Units by a mathematical formulation of a production technology characterized by inputs producing outputs. This method was first introduced in the operational research by Charnes, Cooper and Rhodes (Charnes et al., 1978). Various papers have implemented this method for the assessment livestock farming systems efficiency (Piot-Lepetit, 1998, Gaspar, 2009...). The efficiency score is the result of a multidimensional analysis (i.e. an efficient farm produce more of each outputs with less of each inputs). As we decided to use a radial output distance, the inefficiency score traduces the potential increase of outputs, given their inputs and undesirable outputs levels.

Beyond this classic approach, we implement in this paper a DEA model including undesirable outputs (Koopmans, 1951). Undesirable outputs are weak disposable while classic inputs and outputs are freely disposable. Weak disposability (Kuosmanen, 2005) constitutes a mathematical way to stipulate that if you produce a certain amount of undesirable outputs, you cannot dispose of it freely and all reduction in this amount will also reduce the amount of desirable production. Because of this

relation, the only way to avoid generating undesirable environmental externalities is to refuse producing desirable outputs, following the rule called “null-jointness” (Färe and Grosskopf, 2004).

2.3.2 DEA model formulation

In order to formulate our model mathematically, we consider a set of N farms producing G good outputs and B bads (undesirable) outputs with I inputs, associated with the following index sets: $\aleph = \{1, \dots, N\}$, $\mathfrak{G} = \{1, \dots, G\}$, $\mathfrak{B} = \{1, \dots, B\}$ and $\mathfrak{I} = \{1, \dots, I\}$. We define by: $\mathbf{y}^G = (y^1, \dots, y^G) \in R_+^G$, $\mathbf{y}^B = (y^1, \dots, y^B) \in R_+^B$ and $\mathbf{x}^I = (x^1, \dots, x^I) \in R_+^I$, the quantity vectors of desirable, undesirable outputs and inputs respectively. The production technology is defined by: $T = \{(\mathbf{x}^I, \mathbf{y}^G, \mathbf{y}^B) \in R_+^{I+G+B} : \mathbf{x}^I \text{ can produce } (\mathbf{y}^G, \mathbf{y}^B)\}$. By imposing basic axioms on the production technology (particularly free disposability of inputs and outputs, convexity and variable returns to scale) we add a mathematical structure that leads to measure the efficiency of each farm by the following linear program:

$$\text{Max}_{\lambda, \omega, \theta} \theta \quad (1a)$$

$$\sum_{n \in \aleph} \lambda_n y_n^g \geq \theta y_e^g, \quad \forall g \in \mathfrak{G} \quad (1b)$$

$$\sum_{n \in \aleph} \lambda_n y_n^b = y_e^b, \quad \forall b \in \mathfrak{B} \quad (1c)$$

$$\sum_{n \in \aleph} (\lambda_n + \omega_n) x_n^I \leq x_e^I, \quad \forall i \in \mathfrak{I} \quad (1d)$$

$$\sum_{n \in \aleph} (\lambda_n + \omega_n) = 1 \quad (1e)$$

$$\omega_n \geq 0, \quad \forall n \in \aleph; \quad \lambda_n \geq 0, \quad \forall n \in \aleph \quad (1f)$$

The evaluated DMU (x_e^I, y_e^G, y_e^B) on the right hand side is compared to a benchmark which is defined by a linear combination of the N DMUs that composed the sample on the left hand side. We therefore seek the largest proportional increase of the output vector (, in equations (1a) and (1b)) of the evaluated DMU.

Undesirable outputs are modeled under the weak disposability, represented with an equality in equation (1c), while good outputs and inputs are assumed to be freely disposable (inequality in equations (1b) and (1d)). Variables λ_n and ω_n allow the linear combination to build the efficiency frontier. The null-jointness between good and bad outputs is ensured with the common λ_n in equation (1b) and (1c) though inputs are subject to $(\lambda_n + \omega_n)$. The sum of these two variables is summed to 1 (1e) for each farm because we assume a variable return to scale (VRS) in the dairy sector. The VRS model guarantees that a farm will not be compared to peers with a substantial different production system size.

DEA models are implemented in GAMS (version 23.4).

2.3.3 Outliers detection

In our paper, farms assessed with DEA have been generated by GAMEDE stochastically parameterized. Even if a realistic value is fixed for each parameter, the combination of all these parameters could lead to unrealistic solution. It is important to understand that these unrealistic cases, called “outliers” are not teratologic solutions as in physics terminology, i.e. livestock production systems physically impossible. Indeed, all decision rules and control equation on biophysical process forbid all the teratologic case where a cow eats an unrealistic amount of feed or even a case where a farmer could do two activities in the same time. Outliers in this paper are simply illogical cases where for example a farmer buys a lot of concentrate feeds whereas he has only few cows. Outlier inefficient farms are easily recognizable as they have high inefficiency scores, but it isn’t obvious to identify outliers efficient farms as their score is 1 as the non-outliers efficient farms.

As efficient farms have an impact on all the score of the sample, it is recommended to control if these farms are not outliers. In order to estimate the effect of these outliers on the efficiency score, we implement a method based on the outlier detection research by Simar and Wilson (2008). As many methods in outliers detection, the principle used is to implement the DEA on sub-datasets. We implement many DEA models for each sub-dataset of the original dataset, i.e. without the certainty that all the efficient farms are taken into account. Thus, the maximum inefficiency score is observed when the farm is compared to the whole sample (with all the efficient farms) and according to the random selection of the sub-datasets, we will observe lower inefficiency scores as shown in figure 3.

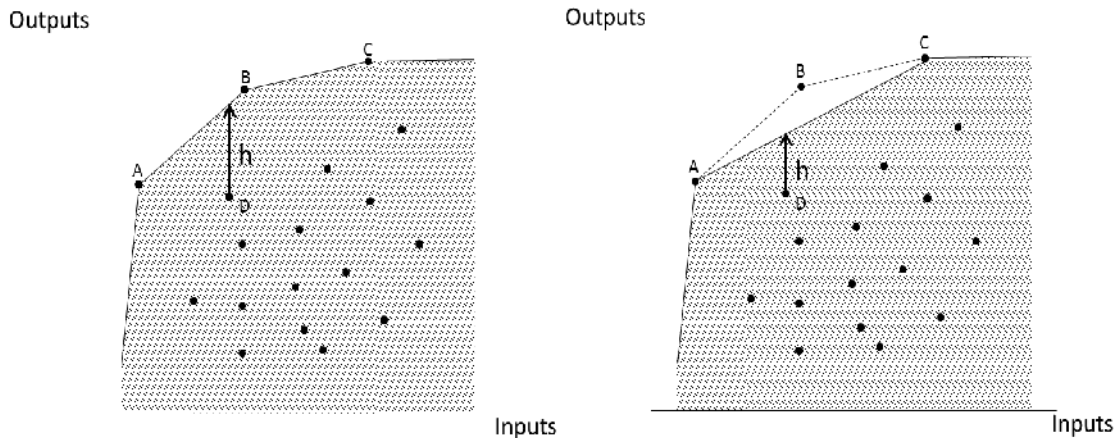


Fig. 3. Influence of outliers on the efficiency frontier and the score of farm D for two datasets: the original complete dataset (left) and a sub-dataset (right)

We implement the robustness model method in order to quantify the impact of potential outliers in the efficiency frontier. For each farm, we implement a DEA model on 100 random sub-samples of 75 % of the whole sample. Thus, results are compared to the efficiency scores where all farms have been assessed among the whole sample.

2.4 Multivariate analysis to explain inefficiencies

Our goal here is to characterize groups of farms with similar eco-efficiency scores (descriptive discrimination) rather than trying to identify a group to affect to a farm (predictive discrimination).

In our case, we have a specific dataset to explore as we have only one variable to explain (the eco-efficiency score) and numerous explanatory variables (input parameters and output indicators of GAMEDE). We propose to implement a between class analysis (Dolédec and Chessel, 1987) in order to analyse the determinants of eco-efficiency score. Between class analysis is a particular case of a Principal Component Analysis, commonly used when there is only a single factor as explanatory variable. We easily understand that in this kind of analysis, the constitution of the groups is highly influencing the results of the analysis. Formally, groups or categories must be exhaustive and mutually exclusive, i.e. each farm must belong to a unique group. In this study, we decided to focus this analysis on farms with an efficiency score between 1 and 2 as they constitute the large majority of the sample (Figure 3). Farms with scores greater than 2 are very scarce and are not taken into account in the multivariate analysis (see 3.2 for further explanations). Five efficiency score classes were made:

- 1 : Efficiency score : 1 (efficient farm, i.e. no improvement possible)
- 2 : score between 1 and 1.1 (0 à 10% of potential improvement)
- 3 : score between 1.1 and 1.2 (10 à 20% of potential improvement)
- 4 : score between 1.2 and 1.5 (20 à 50% of potential improvement)
- 5 : score between 1.5 and 2 (50 à 100% of potential improvement)

Classes reflect the distribution observed in the sample in order to have a homogeneous repartition among the five groups, and also intuitive eco-efficiency range. A large number of farms have small eco-efficiency scores, so smaller intervals were fixed for classes of lower eco-efficiency scores.

Multivariate analysis is implemented in R (3.0.0).

3 Results

3.1 DEA dataset

Conventionally, the DEA dataset is presented in the material and methods part, but in our case, as it is a result of the GAMEDE data generation, we present the retained variables for the efficiency frontier in the introduction of the results part. As emphasized in Figure 2, a dataset is built from Gamede parameters and outputs for the DEA analysis. A statistic overview of data selection for the frontier efficiency analysis is presented in Table 3. Milk production is considered as the major output of dairy production systems in La Reunion as it represents the main part of farmers' revenue. Forage management is a key point in the eco-efficiency and specifically in nitrogen management. Since we explore the realm of possible in strategies of eco-efficiency, we consider forage sell in the DEA dataset, in order to take into account the production systems with large forage crops which produce more forage than necessary for herd's nutritional needs. Nevertheless, it is worth noting that forage sell is limited by GAMEDE decisional system and forage sell is activated only if herd's needs are met. Nitrogen balance (N farm-gate balances) is considered as the only undesirable outputs in the production technology. In the DEA dataset, nitrogen balance is not expressed by Ha, as it would be redundant with the consideration of total surfaces as an input. Concentrate feed and mineral fertilizer are considered as inputs as they represent the trade-off between an alimentation based on concentrate feeds or on an intensive use of forage surfaces thanks to mineral fertilization. Energy income includes direct energy consumption as petroleum, electricity and natural gas. Energy income also comprises indirect energy required to extract, produce, transform, package and transport other farm inputs (Vayssières et al., 2011) thanks to a "cradle-to-farm-gate" life cycle analysis approach. Lastly, total

surfaces (sugar cane and grassland) and total labor are considered as two classical inputs in DEA analysis.

Table 3

DEA dataset descriptive analysis (n=5000)

Inputs(x)/ desirable outputs (y ^g) bad outputs (y ^b)	Units	Mean	Standard deviation	Min	Max
Milk production (y^{g1})	Liter	201733.8	125059.5	5508.8	702922
Forage sell (y^{g2})	Kg of fresh matter	847144.2	604846.2	228	2605976.7
Nitrogen Balance (y^{b1})	Kg of nitrogen	5052.9	2875.48	0.78	2875.48
Herd (x¹)	Animal	79.8	41.7	1.7	150
Concentrate feed (x²)	Kg	214855	119450.6	10580.4	640866.7
Mineral fertilizer (x³)	Kg	29068.3	20904.3	49.2	119650
Total Surface (x⁴)	Ha	33.9	15.6	0.3	69.56
Labor (x⁵)	Hour	5505.9	1778.1	1682.2	12201.8
Energy income (x⁶)	MJ	2702333.4	1018256.1	331577	6067640

3.2. DEA results: eco-efficiency score of simulated farms

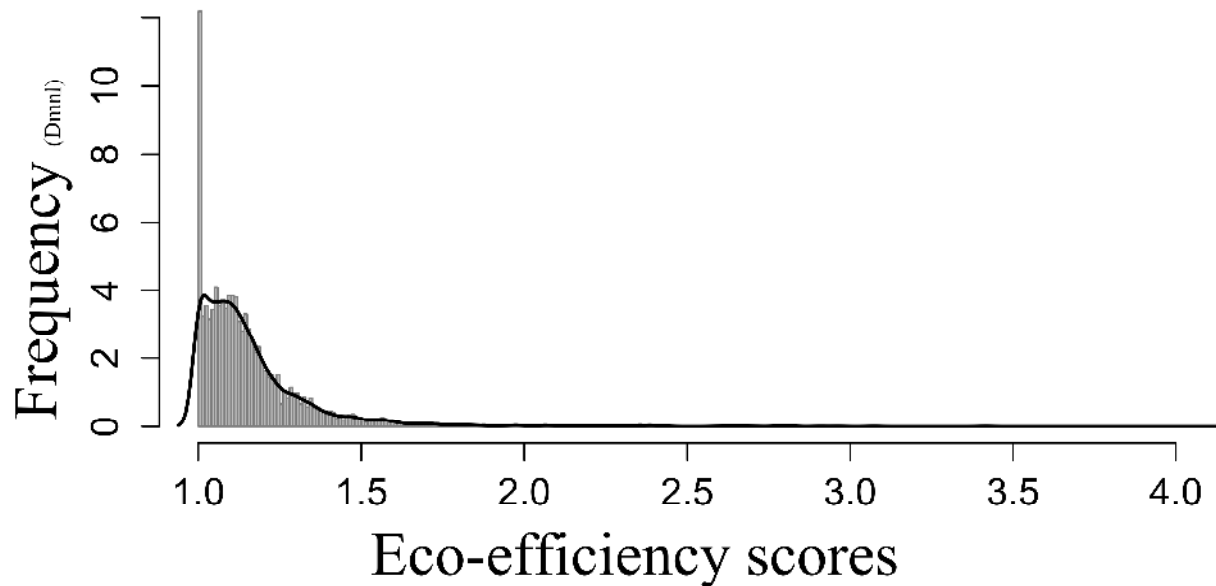


Fig. 3. Distribution of the efficiency scores (5000 simulated farms, Dmnl=Dimensionless)

The linear program presented in 2.3.2 is implemented for each simulated farms. The progress margin in milk production and forage sell is measured according to the distance with the frontier efficiency. Figure 3 exposes the distribution of progress margin in percentage and kernel density estimation (black curve). We can clearly see the efficient farms which constitute the peak at 0 % potential progress margin (461 farms efficient among all the simulated farms). Secondly, it appears that most of the farms have eco-efficiency scores 1 and 2. Finally, figure 3 exposes a horizontal line characterized by dotted outlier's presence, with a maximum value of potential eco-efficiency improvement by 383 %. This distribution of eco-efficiency justifies our choice to consider farms with

eco-efficiency scores between 1 and 2 in 3.3. Nonetheless, it is essential to ensure that outliers don't impact the efficiency frontier, and thus, the score of all the simulated farms.

3.3. Outliers impact on efficiency scores and model robustness

We express in table 1 the mean efficiency score in order to compare it between the two types of models (robust and non-robust). In the non-robust model, we observe a score of 1.1755, i.e., a potential raise in milk and meat production by 17.55% with reference to the current level of production. When we use the robust model to reduce the outlier effect, we observe a slight reduction of the score (by - 1.79 %), corresponding to bigger potential raise in production. This result doesn't mean that data generation by GAMEDE hasn't generated outliers, but that outliers affect poorly the efficiency frontier and the eco-efficiency scores. We can conclude that outliers generated by GAMEDE are inefficient. It is coherent with the important level of inefficiency calculated for some farms. For 1.15% of the farm, the scores are between 2 and 3.83 i.e. production can be improved by more than 100%. GAMEDE generate outliers but always highly inefficient, and as a consequence doesn't affect the structure of the efficiency frontier (further reflections are presented in the discussion about the outlier management in the case of farm-model based dataset).

Table 1

Outlier's impact on the efficiency frontier.

Model built on the whole dataset	Model build on the whole data set			Outliers impact
Score (mean)	number of draws (b)	sub-dataset size (m)	Score (mean)	Difference (%)
1.1704	100	75%		

3.4. Eco-efficiency determinants exploration with multivariate analysis

Figure 4 shows the graphic exploration of the between class analysis and emphasizes an eco-efficiency gradient along the horizontal axis (i). Indeed, efficient farms are situated on the left side of the graphic while inefficient farms are at the opposite side. With lower parts of figure 4, it is possible to characterize with all GAMEDE indicators (ii) and GAMEDE inputs parameters (iii) the horizontal axis which define an eco-efficiency gradient. Eco-efficient dairy farms in La Réunion appear to have high gross margin. This economic performance is based on important part of feed concentrate in the alimentation. Indeed, management practices on feed concentrate alimentation for the three practical seasons considered are all intensive for eco-efficient farms. The high dairy productivity observed for eco-efficient farms supports this remark and testify of intensive dairy system production. Here, it is important to point out that eco-efficiency takes into account the total amount of concentrate feeds as inputs, so we can find efficient farms at any levels of concentrated feeds use. This total amount of concentrate feeds must not be confused with the management practices to feed dairy cows during the three seasons with feed concentrate. Conversely, we can say that using feed concentrate during only one season is not improving the eco-efficiency. Exploration of variable constructing the horizontal axis also emphasizes the importance of alimentation-self-sufficiency in the production system and the efficient use of forages crop surfaces. Actually, GAMEDE calculates an indicator called "Feed self-sufficiency" which reflects the proportion of feed forage produced on the farm. This indicator is closely linked to eco-efficiency as the amount of UF produced by Ha of grassland and the total surface of grassland. All these variables reveal that eco-efficient farms have an intense forage

production activity to support their own feed demand. They optimize the potential of their large surfaces of grassland to avoid as much as possible to be dependent of external sources of forage. This strategy also explains their eco-efficiency as it allows them limiting their nitrogen inputs as forage purchase and thus, improves their nitrogen balance (even if obviously forage crop necessitates an increase in fertilizer use). Energy exportation (composting, manure sell...) appears also as a characteristic of eco-efficient farms. To sum up, eco-efficient farms appears to have efficient use of concentrate feeds and develop as much as possible their feed self-sufficiency with their crop production. Inefficient farms situated on the right part of fig. 4 are closely linked to many parameters inherent to the meat production. Indeed, GAMEDE provides an indicator called “System Biological orientation” for each simulation farms and this indicator appears to be representative of the inefficient farms. This information is corroborated by the two structural parameters “Animals sold” and “Lended calves” (calves are temporally given to the cooperative for them to be grown in the best conditions and fully develop their dairy potential) which emphasize the significance of the meat production in these inefficient systems. These results can also be explained by some modifications in the herd size strategy. Indeed, an important amount of animals sold could reveal a farmer’s desire to reduce the quantity of dairy cows. Conversely, an important number of calves temporally given to the cooperative could be an indicator of farmer’s wish to increase the dairy herd size in a short-term period. Of course, results would have been different if meat sold would be considered as an output, nevertheless, we decide to focus in our output selection on the dairy and forage production.. This issue of technology production definition and its impact on the results will be discussed in 4.2. Inefficient farms are also characterized by a GAMEDE indicator called “Crop-livestock interaction” which specifies the degree of integration between livestock production and crop production (essentially the recycling of manure as a fertilizer for crop production, forage sell, manure exportation). This remarks is coherent with the other indicator called “Fertilizer self-sufficiency” also characteristic of eco-inefficient farms. These results could appear as contradictory as manure management is most of the time considered as a good practice for the eco-efficiency but it must be noted that the total labor is considered as an input in our DEA dataset. Thus, even if the integration of manure in the crop production is without a doubt benefic for the nitrogen balance, it may also increase the amount of labor required and decrease the global eco-inefficiency. These farms have intensive grassland exploitation as the two indicators of productivity (grassland and ensiled grassland) reveal good performances. Nevertheless, this strategy is judiciously managed by the famers who choose to let important interval between two harvest periods during the summer season. This statement emphasizes that eco-inefficiency is linked to the dairy systems based on small grassland in La Réunion.

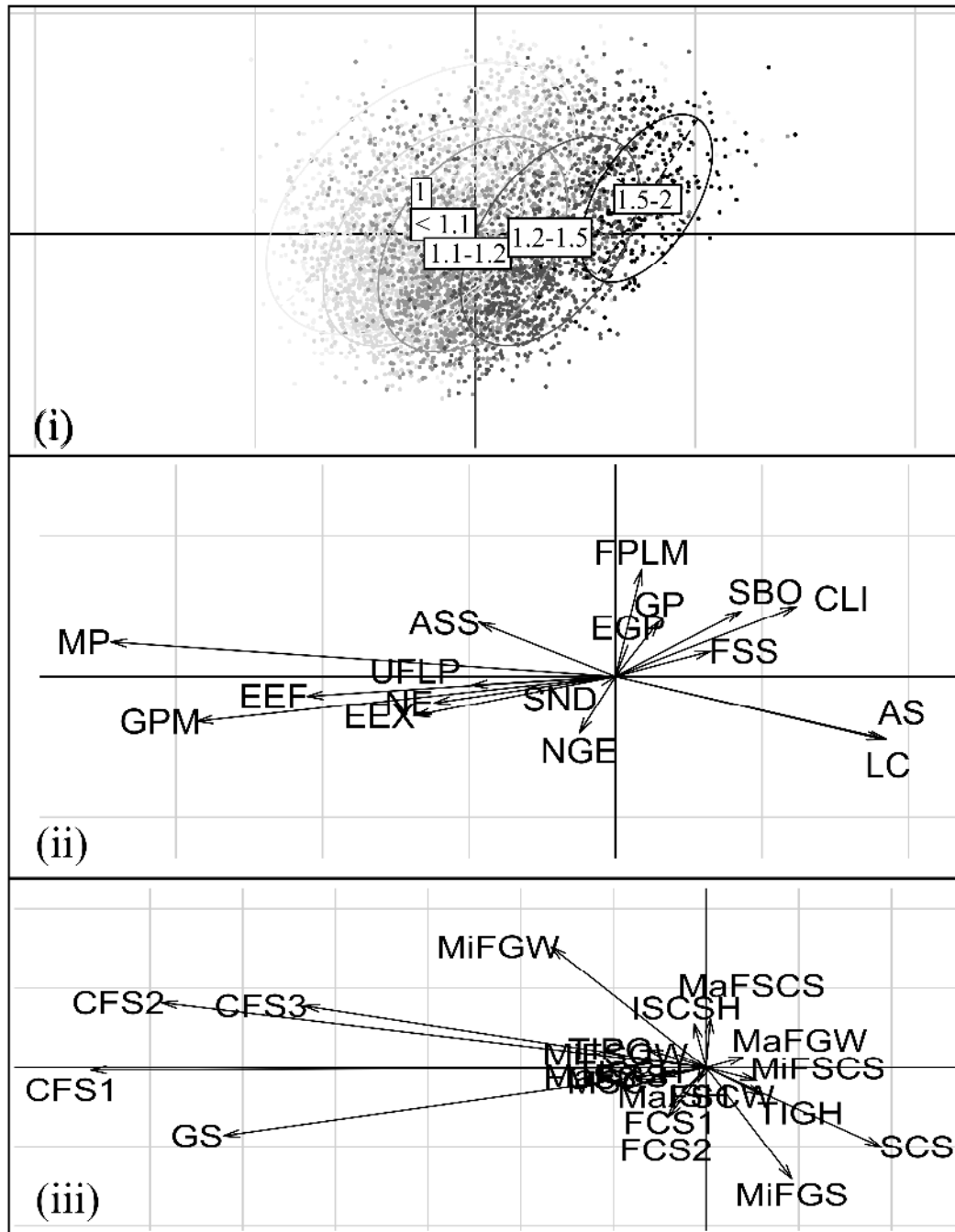


Fig. 4. Graphic exploration of the efficiency score diversity (Between Class analysis). (i) Eco-efficiency classes dispersion; (ii) Gamede indicators contribution to classes' dispersion; (iii) Gamede parameters contribution to classes' dispersion.

The shape of each circle characterizing the efficiency group in fig. 4 (i) indicates an intra-group variability explained by the vertical axis. This axis is mainly built by two GAMEDE indicators: energy consumption per liter of milk produced and nitrogen gaseous emissions. Thus, even if energy indicators are also discriminant for inter-group variability, we note that various levels of energy use are observed among each groups of homogeneous degree of eco-efficiency. In the same way, while eco-efficiency characterization has underlined different management practices in nitrogen use through various forage crop strategies, we see that gaseous emissions are heterogeneous among each group.

This result is not surprising as gaseous emission are linked to various factors, both managerial (manure management) and structural (manure storage capacity).

3.5. Crossing frontier efficiency indicators with GAMEDE indicators

A graphical exploration of GAMEDE outputs gives information about the characteristics of the simulated farms. Moreover, we can illustrate the eco-efficiency score on the graphic as in fig. 5 in order to see the accordance of the two types of indicators. Fig.5 shows a relation between nitrogen efficiency and energetic efficiency. The positive relation between those two GAMEDE indicators emphasizes the link between nitrogen management and the overall use of energetic income. For example, we can assume that manure optimization practices allow reducing mineral fertilizer purchase and thus, reduce energetic balance as mineral fertilizer income greatly impact life cycle analysis. Projection of eco-efficiency score on Figure 5 shows that most of eco-inefficient farms display low energetic efficiency and nitrogen efficiency levels. The correlation between energetic efficiency and eco-efficiency score seems very important but we must note that energetic income has been taken into account as inputs in the DEA model, and eco-efficiency score are thus directly impacted. Nonetheless, mineral fertilizer income has also been taken into account in the DEA model, but nitrogen efficiency includes all nitrogen flows in the dairy production system (animals sell, manure management, crop fertilization...).

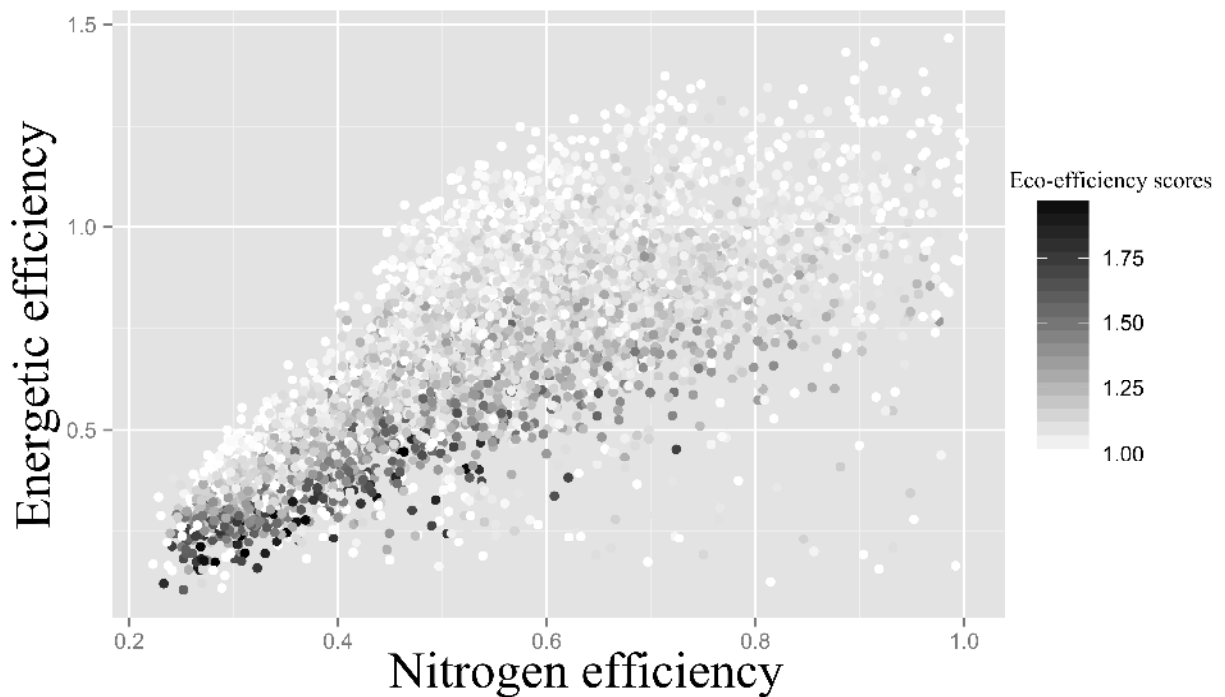


Fig. 5 Indicators exploration of simulated dataset regarding the multidimensional eco-efficiency score.

The presence of efficient farms in the lower-left part of fig. 5 could seem counter-intuitive as they are deemed as efficient under the DEA method and still have low nitrogen and energetic efficiency. This result is due to the linear program structure of the DEA program and is discussed in 4.2.

4 Discussion

4.1. Main assets and methodological advances

Simulation-based optimization has already been performed in environmental issue (Matott et al., 2012). Similarly we propose to call our methodology Simulation based-DEA (SBDEA) and we argue that the one we propose here allows exploring deeper the diversity of the production systems and the determinants of their eco-efficiency. DEA calculates whether a farm is efficient or not and if the farm is deemed inefficient, the method determines a degree of inefficiency. Here is one of the major asset of the DEA method: where most optimization programs try to reach targeted value based on environmental standards or targeted value, DEA assess the potential progress margin according to farms with the same level of inputs (for an outputs raise) or the same level of outputs (for an input reduction). In these terms, the eco-efficiency score attests of a realistic multidimensional progress margin for a considered farm.

Eco-efficiency assessment studies of agricultural systems are classically based on two types of dataset depending on the scale and the research objectives:

- Large public dataset available online as the FADN (Farm Accountancy Data Network) or the FAOSTAT database. These data are frequently used by macro-economists, and provide various economic, social and environmental indicators. Nevertheless, it fails to give specific details on the production system as farm structure and management practices (for instance feeding and manure management practices are determinant for the efficiency of livestock systems).
- Agronomic studies based on small samples in specific pedo-climatic and socio-economic contexts. These studies describe accurately the production process but pursue different objectives and the results can hardly be compared between studies. These dataset are mainly used in agronomic research for their robustness but critics are often made about the non-representativity of the sample and thus, the difficulty to generalize the results.

The proposed methodology has the advantage to respond to the two objectives, i.e. i) to dispose of large datasets on production systems to increase the level of representativeness and accuracy in the description of the production process, and ii) to dispose of robust explanatory variables to explain determinants of the efficiency of the production process. This is particularly relevant for the global reflection on the efficiency gap observed in various contexts and the necessity to reduce it. The FAO program “closing the gap efficiency” (FAO, 2012) rightly states that eco-efficiency analysis in heterogeneous livestock systems around the world is a key issue to feed 9 billion people in 2050: “[...] improve natural resource use efficiency by the transfer of technology and knowledge from the world’s most to least efficient production systems”. But by focusing on technology transfers, FAO implicitly assumes that generic determinants of eco-efficiency can be found for the different agronomic, socio-economic or cultural contexts encountered in the world. On the contrary, we suggest that the determinants of eco-efficiency in various territories are generally not the same and the exploration of the realm of possible production systems with frontier efficiency methods is a judicious way to determine the endogenous factors determining the eco-efficiency. For instance, in our study case, the feed self-sufficiency appears as a key element in the eco-efficiency of dairy of La Réunion but this factor could be irrelevant in another context where, for example, large productions of forage crop are impossible due to limited rainfall. In the same way, feed concentrates consumption is closely linked to eco-efficiency in this insular territory but it can be deemed as useless in a territory with less

pressure on land and where soybean or cereal crop can be cultivated on large surfaces. The research presented here is a first step in the exploration of using a whole-farm model to generate data simulated farms used for frontier efficiency analysis. Further implementation of SBDEA with other models relevant for other agronomic contexts will shed light on the heterogeneity of intra-systemic eco-efficiency determinants.

4.2. Critical methodological points

This section focuses on the key points that have to be rigorously controlled in order to conduct comparable studies in other contexts.

The first critical point is the stochastic data generation and more specifically two of its components: the choice of the structural and managerial parameters and the setting of the lower and upper bounds for each of them. Indeed, whole-farm model includes various parameters and it is impossible, for computerized reasons (length of simulations) to use all of them for the random parameterization. Moreover, even if it was possible to select all the parameters, some of them would be redundant and will be useless to accurately define the eco-efficiency determinants. In our paper, the choice of the parameters to be randomly fixed has been based on a deep knowledge of the dairy production systems. As we explained it above, GAMEDE was co-designed with farmers and the participatory methodology involved different complementary types of surveys (immersion, individual visits, meetings, and visual interactive simulations (Vayssières et al., 2011)). This methodology has allowed the researchers to understand deeply the interactions between the management practices and the farm performances to solve a nitrogen management issue. On the strength of this knowledge, we have been able to assume hypothesis on the key parameters in the eco-efficiency and thus, to make a restrictive choice of parameters. For each parameters, a lower and an upper bound has been fixed. Once more, these bounds are based on observed ranges and local expert knowledge. In other words, it is necessary to know the current levels of these parameters (and most of all the extreme values) but also the potential values unobserved but which appears as possible in the considered agronomic and socio-economic context. For example, even if it is unlikely to find a dairy herd of 0 or 1 cow in La Réunion, we decide to fix the lower bound of the herd parameter at 0 in order to “give the possibility” to simulate a farm with no herd, specialized in forage production (that can be sold). We clearly see here why the upper and lower bound specification is a key point in our methodology: it must reflect the current levels of these parameters in a given context but also let the possibility for the whole-farm agronomic model to explore new production systems not observed on field.

The second critical point of our methodology is the definition production technology (from an economist point of view and with reference to the DEA method), i.e., the choice of inputs, outputs and undesirable outputs. Indeed, in operational research, the choice of the technology production is mainly limited by the dataset availability. However, in the case of simulated data by a whole-farm agronomic model, a lot of data are available and economist and agronomist have to found an agreement on a reasonable and sufficient number of variables characterizing the production process. In our example, we have seen that the exclusion of the meat production has impacted the level of eco-efficiency of dairy farms with a meat production activity. Moreover, figure 5 emphasize that the technology production definition lead to unusual results as the presence of efficient firms which display low levels of nitrogen and energetic efficiency. Indeed, to be deemed as inefficient, a farm must have peers that produce more of each output with less of each input and bad output. Thus, we easily understand that a farm can be deemed as efficient only because it is efficient on one of the various dimensions considered in the production technology. This remark highlights the multi-dimensionality

of the DEA score and explains why it is particularly rare to obtain clear and significant relations between scores and sustainability indicators on a two-dimension graphic particularly.

Obviously, from an agronomic perspective, it seems very difficult to reduce a complex production system gathering dairy production, meat production, other agricultural activities, and sometime other types of revenue (materials renting, bull loan...) in such a limited numbers of data. In developing countries, where most of production systems are mixed (Herrero et al., 2010), defining the technology production is challenging. Agronomist methods as typologies must emphasize few variables characterizing each production systems and, this way, allows choosing inputs and outputs representative of each types of livestock systems. This choice is a major condition for a multidimensional analysis of the eco-efficiency. The production technology must rely on the knowledge of agronomist on the assessed production system and also on the experience of economist to define a production process for a DEA method.

4.3. Limits and recommendations for further studies

During its presentation (Berre et al., 2012b), our methodology aroused strong interest and discussion, and in order to help further implementation of the method we formulate here the main improvement points for further studies.

Even if we found a methodological way to assess the influence of outliers on the frontier efficiency, their generation by a randomly parameterized whole-farm model appears as the major necessary research to improve the proposed methodology. Unfortunately, this drawback seems to be intrinsically linked to the purpose of the method: exploring the realm of possible of livestock production system in a given context. Indeed, as we allow a random choice of value for each parameter between extreme bounds, the generation of unrealistic production systems is unavoidable. In trivial terms, we can argue that the generation of outliers is a lowest cost for the exploration of new eco-efficient livestock production systems. In the perspective of further implementation of a whole-farm model combined with a frontier efficiency method, we formulate two recommendations to manage outliers generated:

- Efficiency frontier methods give a potential eco-efficiency score based on the efficient production systems. Thus, it is crucial to ensure that outliers don't impact the frontier. In our paper, we show that sub-sample methods classically used in operational research are very useful to quantify the impact of outliers on the frontier, and thus on the score of all the exploitations considered. Another path of research could be the strict analysis of the efficient farms to be sure that inefficient outliers are excluded of the final dataset assessed.
- A second key point is the necessity to be sure that biophysical process and decision rules constraint the agronomic model in order to avoid physically impossible solution. Therefore, outliers are not physically impossible but simply logically inconsistent. This consideration is important because without these bounds in the whole-farm agronomic model, we would have some efficient outliers and all DEA scores would be affected.

As we explained above, Data Envelopment Analysis is not only an optimization method but a microeconomic tool based on mathematic and economic hypothesis. Further research with important dataset generated by agronomic model should explore deeper the potential of frontier efficiency method to widen the eco-efficiency combining research. For example in this first study, we have implemented a primal model, i.e., a model where eco-efficiency is tackled from a quantitative point of view. DEA also allows exploring eco-efficiency from an economic point of view, and recent publications have demonstrated that it could be very helpful to price environmental externalities (Berre et al., 2012a; Hernández-Sancho et al., 2010). Indeed, exploration of shadow prices of undesirable outputs on large datasets in an agronomic context could be helpful in the establishment of

agri-environment measures. The implementation of directional distance function could also bring a new perspective on the way to reduce eco-inefficiency in an agronomic context. These functions specify the direction to reach the frontier efficiency. For example, we can imagine measuring eco-efficiency scores for farmers legally obligated to reduce one of their inputs (e.g. reduce mineral fertilization after groundwater contamination), or one of their bad outputs (e.g. reduce nitrogen surplus to maximum levels policies). Combined with simulated dataset covering the realm of possible, directional distance function could be a very interesting application of our first methodology proposal as it will distinguish different eco-efficiency determinants according to the direction chosen to improve eco-efficiency.

Regarding the implementation of the proposed methodology, an advanced knowledge in three programming languages (Vensim, GAMS and R) is required. Presently, data generation, eco-efficiency analysis and eco-efficiency determinants exploration are implemented separately and each step requires data format conversion to fit software's specificities. A major improvement in our methodology would be to gather all coding tasks in one intuitive programming language with a simplified user interface. Indeed, in order to catalyse interdisciplinary research in agro-ecology, various platform as SEAMLESS (van Ittersum et al., 2008), ModCom (Hillyer et al., 2003) or RECORD (Bergez et al., 2013) has allowed to assembly, as "Lego blocks", broad range of computer languages. Our methodology emphasizes the recommendation of Bergez et al. (2013) to develop further work to link these agronomic platforms " [...] with scientific-software environments such as Matlab or GAMS to foster collaboration with economists". These more integrated approaches has the main goal to avoid the construction of new model *ex nihilo* by the capitalization of existing models even if some modification are required to allow their utilization among a global generic framework. In order to provide an integrated assessment tool of eco-efficiency, further work in a global framework gathering agronomic models, frontier efficiency methods and graphical exploration, appears essential to circumvent the use of multiple programming languages.

Finally, the last recommendation concerns the necessity to explore the diversity of new environmental indicators. We can cite for example the biodiversity impact indicators, soil acidification, eutrophication or indirect lands used. In our case, if the input "land" had included the indirect land (i.e. the crop land necessary to produce the concentrate feeds) results would have been probably different as important consumers of concentrate feeds would have been strongly impacted. Life cycle analysis indicators, as greenhouse gases emission, can be easily integrated in the proposed methodology as many studies have already explored the combination of LCA and DEA (Nasiri and Huang, 2008, Vázquez-Rowe et al., 2012).

5 Conclusion

This paper describes an original methodology combining farm simulation models developed by agronomists with frontier efficiency analysis, classically used by economists. The methodology is illustrated to identify pathways for ecological intensification of dairy farms in Réunion. A whole-farm model, GAMEDE, was used to generate large dataset that were reused to analyze the eco-efficiency of dairy farms in La Réunion Island with the DEA method. Regarding our study case, we emphasize that the specific context, mainly characterized by the isolation of the territory and the land scarcity, explains why intensive systems appears as the most eco-efficient. This study shows that using a whole-farm agronomic model to simulate production systems allows a deeper exploration of the eco-efficiency determinants than classically done with pure efficiency frontier analysis. These classical efficiency frontier analysis are frequently incomparable when realized for different contexts because

datasets are not constructed on the same information, and they don't provide a full comprehension of the intrinsic determinants in the production process (lack of explaining data as management practices or decision rules). "Closing the efficiency gap" is a pillar of the FAO agenda, and transfer of technology from the most efficient producers to less efficient ones in similar agro-ecological and socio-economic conditions is still strongly promoted. Consequently, we recommend taking special attention in the identification of all the endogenous determinants of eco-efficiency in the different agronomic contexts. Our methodology is a first step in the promising combination of agronomic and frontier efficiency models. After this first experience, we recommend paying attention to the data generation process, and specifically the parameters choice and ranges, appears as the keystone to ensure agronomic data consistency. Regarding the frontier efficiency analysis, the definition of the production technology must be consistent from an economic perspective but also coherent with the agronomic context. The proposed methodology is interdisciplinary. In particular, its implementation requires a close collaboration between agronomists, economists and modellers, because heterogeneous knowledge are mobilized. An expertise on agricultural systems, knowledge on specialized concepts and methods from economy sciences, and various skills in modelling (model design and development, simulation) are needed to implement the proposed methodology. (programming software, data definition...). Modelling platforms, as RECORD (Bergez et al., 2013) and MODCOM (Hillyer et al., 2003) which gather and facilitate the reuse of various published and recognized agronomic models, are potentially powerful tools to democratize the proposed methodology.

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